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(Article begins on next page)

A network approach to investigate the aggregation phenomena in sports

Luca Ferreri^{1,2} Fabio Daolio⁴ Marco Ivaldi³
Mario Giacobini^{1,2} Marco Tomassini⁴

¹Complex System Unit, Molecular Biotechnology Center

²Department of Animal Production, Epidemiology and Ecology, Faculty of Veterinary Medicine

³Motor Science Research Center, S.U.I.S.M

University of Torino, Italy

⁴Faculty of Business and Economics, Department of Information Systems

University of Lausanne, Switzerland

CS-SPORTS

Paris 12th August 2011

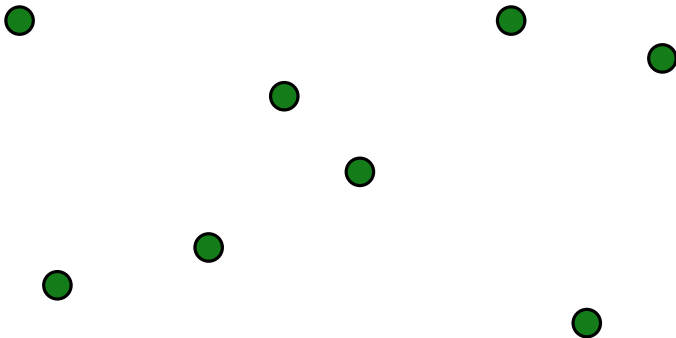
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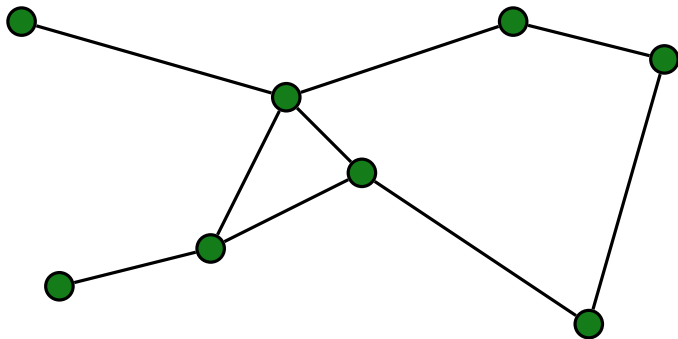
Network: definition

A network is given by a set of **nodes**

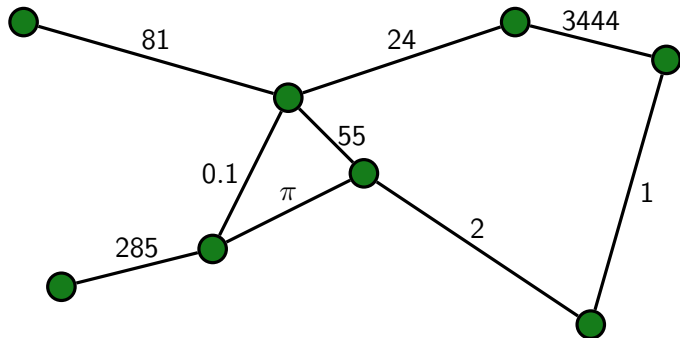


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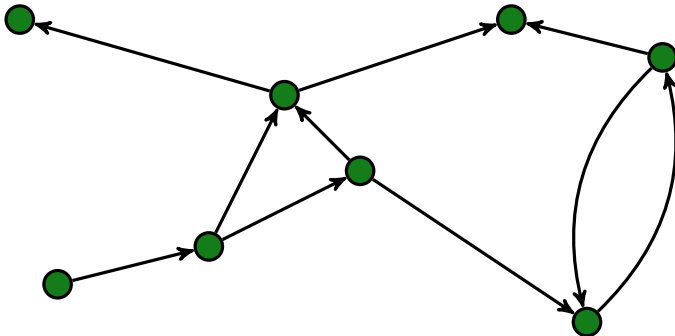
A network is given by a set of **nodes** and of interactions among nodes called **edges**



Weighted Networks



Directed Networks



Complex Networks: Nodes Centralities

- **degree-centrality**: the importance of a node grows proportionally with its degree

Complex Networks: Nodes Centralities

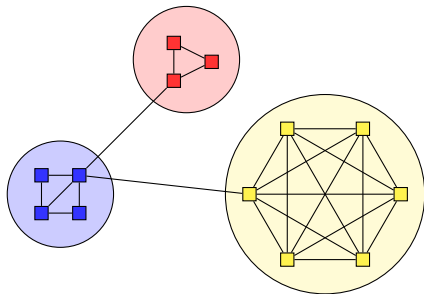
- degree-centrality: the importance of a node grows proportionally with its degree
- **betweenness-centrality**: the importance of a node given by the number of paths of minimum length that cross the node

Complex Networks: Nodes Centralities

- degree-centrality: the importance of a node grows proportionally with its degree
- betweenness-centrality: the importance of a node given by the number of paths of minimum length that cross the node
- **eigenvector-centrality**: the importance of a node is proportional to the sum of the importance of all vertices that point to it (Newman 2003):

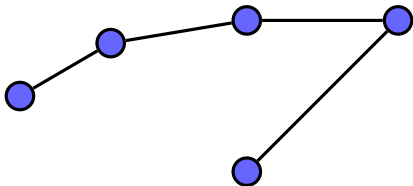
Complex Networks: Communities Detection

A community is defined as a subnet having few number of edges departing from it



Complex Networks: Distance among Nodes

Distance among nodes is defined as the minimum number of edges necessary to connect two nodes.



The shortest path in network is called the **radius** of the network while the longest is the **diameter**. In real world network it has been observed the **small-world** phenomena: a small diameter compared with the number of nodes.

Complex Networks: Assortativity

We try to answer the question whether nodes prefer to connect with their similar (assortative behaviour) or not (dissortative). In particular for node similarity we intend degree similarity.

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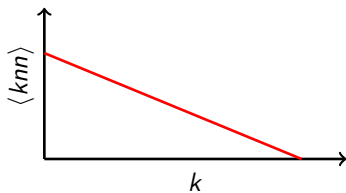
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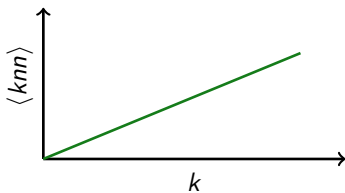


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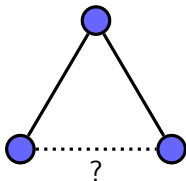
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Complex Networks: Clustering Coefficient

The clustering coefficient of a node is a measure of how its neighbors are connected.



Complex Networks: Heterogeneity

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a measure of the **heterogeneity** is given by:

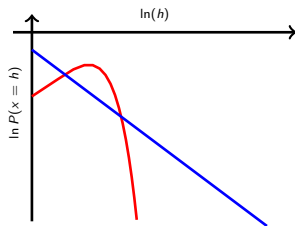
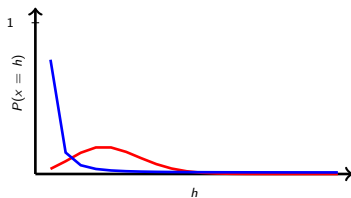
$$\frac{\langle k \rangle}{\langle k^2 \rangle}$$

Complex Networks: Heterogeneity

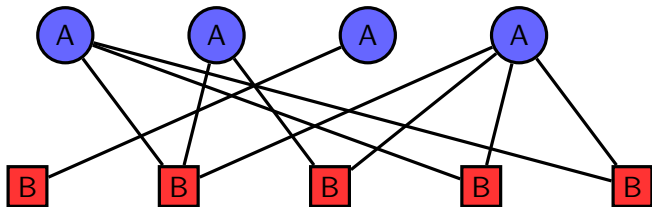
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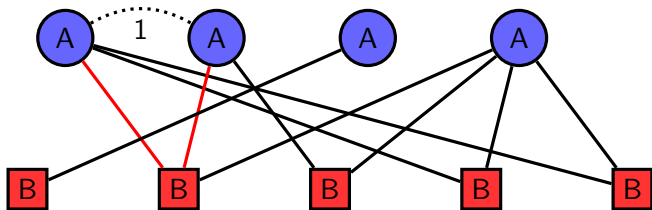
Bipartite Networks



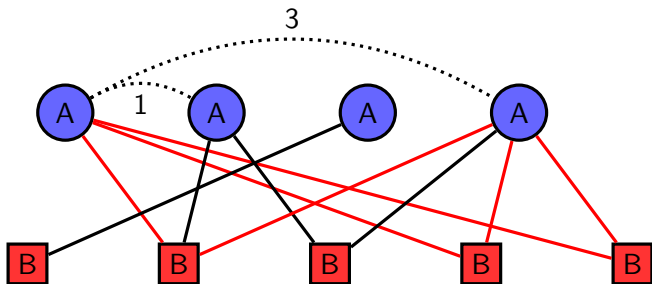
Many example:

- co-authorship network;
- diseasesome;
- heterosexual contact network;
- vector-borne disease network;

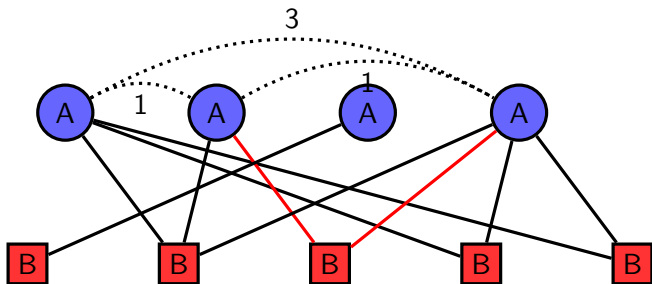
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Bipartite Networks

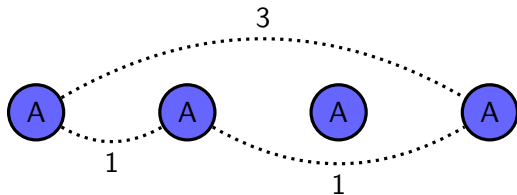


Bipartite Networks

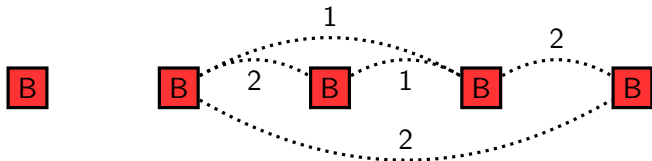


Bipartite Networks

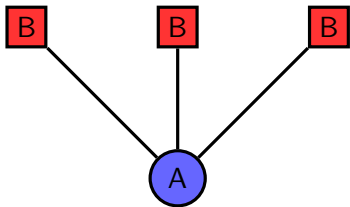
The A -projection



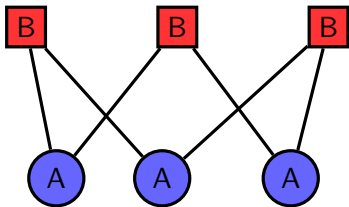
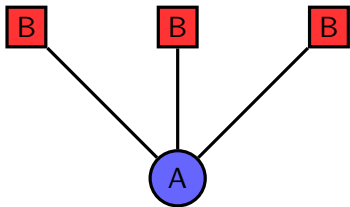
the B -projection



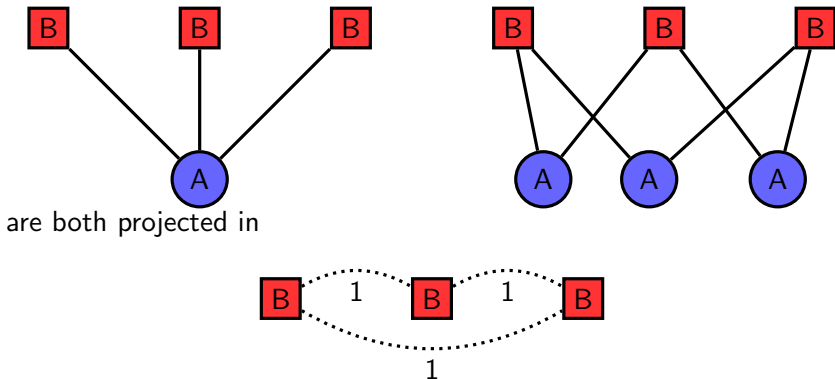
Bipartite Projection is less informative



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We-Sport: a sparse network

We consider a snapshot of the entire network:

- 1680 athletes

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we define the density for bipartite network as:

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- the first have 1679 athletes and 239 sports

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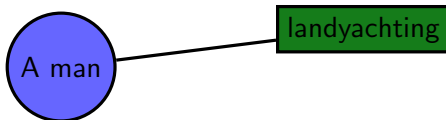
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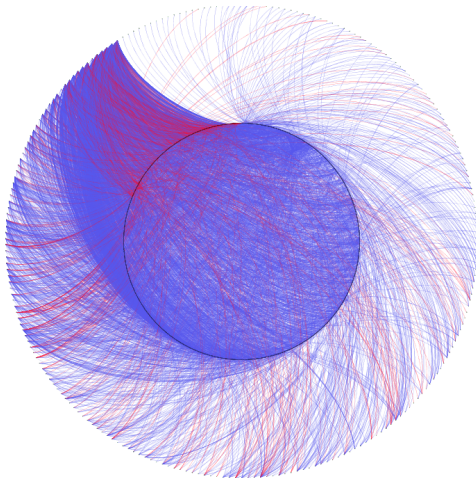
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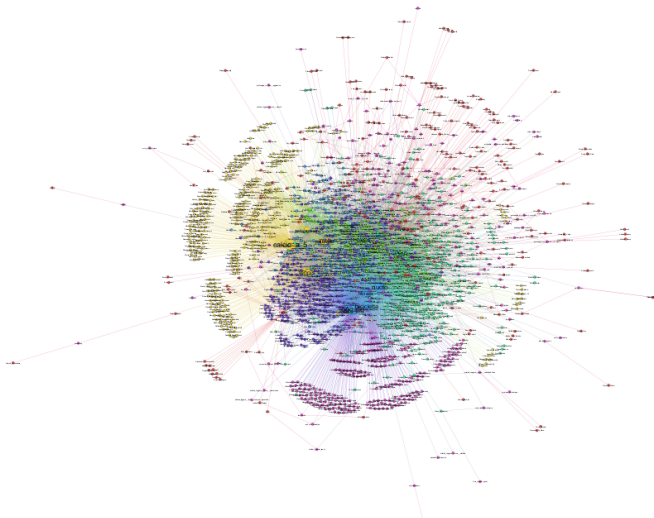
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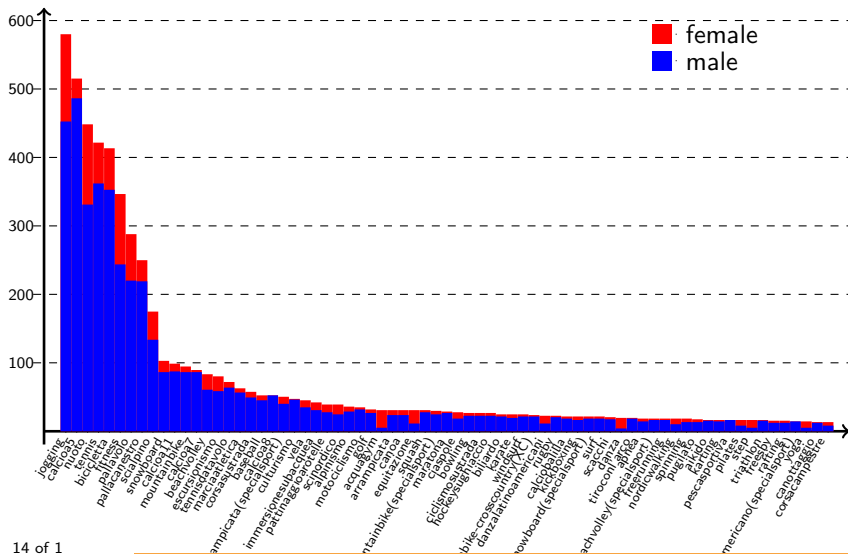
Graphical representation of bipartite We-Sport network



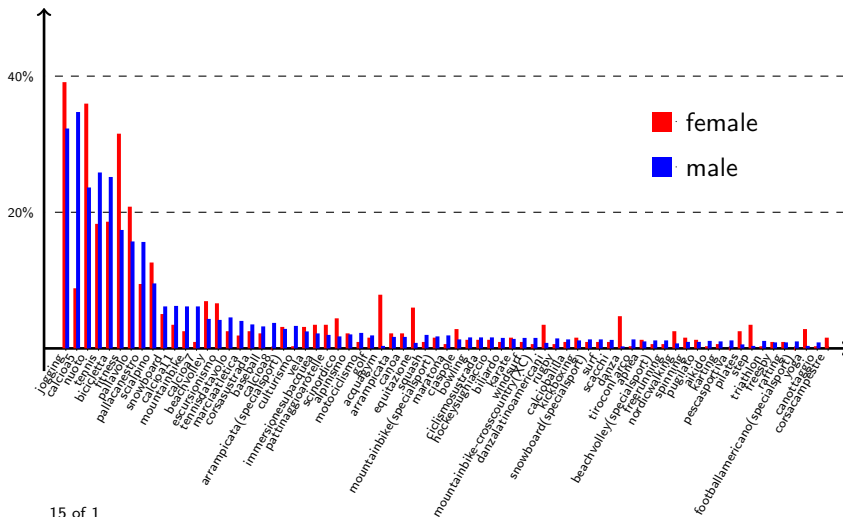
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The 70 most played Sports



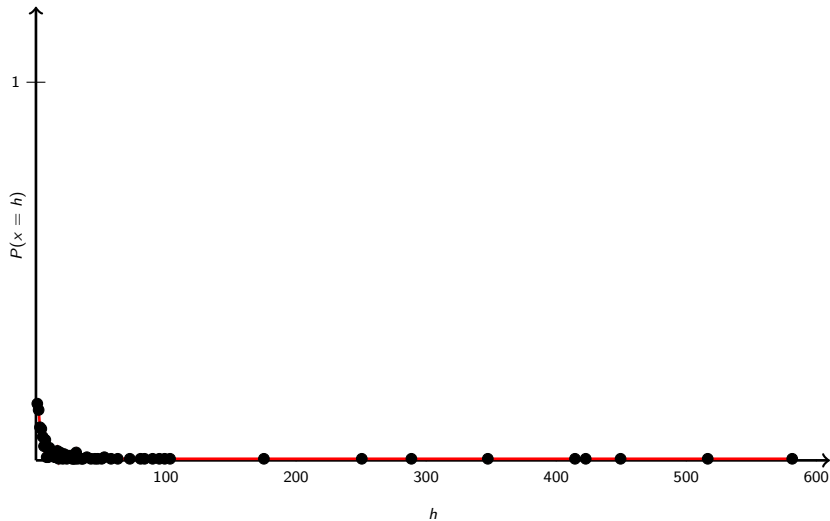
The 70 most played Sports: gender frequencies



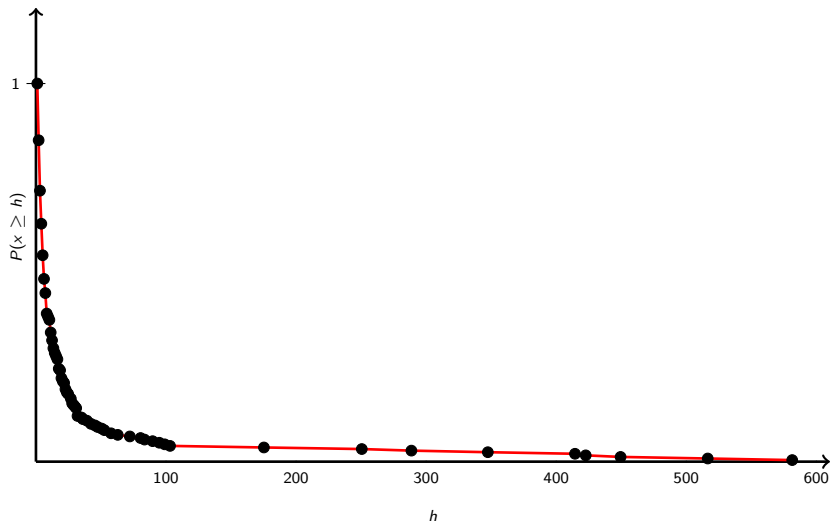
A complex network

partition	mode	median	$\langle k \rangle$	$\langle k^2 \rangle$	$\frac{\langle k \rangle}{\langle k^2 \rangle}$
sport	1	5	25.54	$6.183 \cdot 10^3$	0.0041
athletes	1	3	3.63	23.78	0.1530

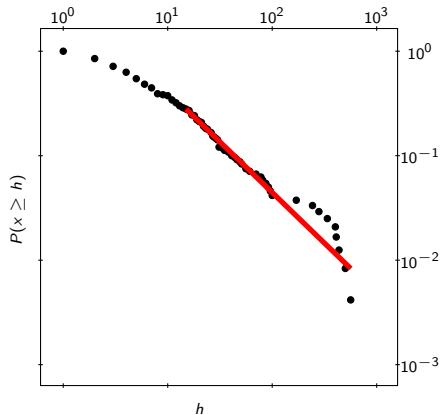
Degree distribution: sport nodes



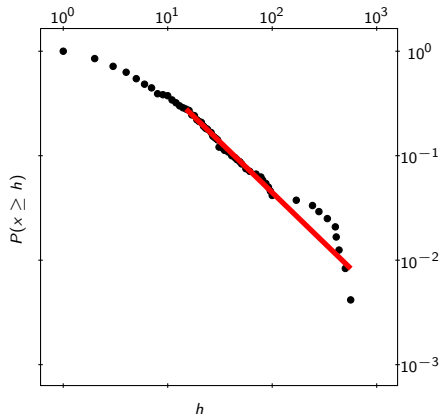
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Degree distribution: sport nodes logarithmic scale



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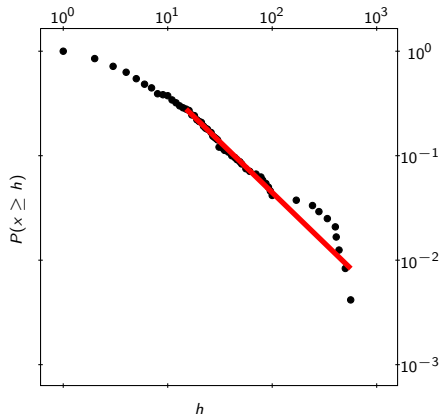


$$\alpha = 1.96$$

$$x_{\min} = 15$$

$$p\text{-value} = 0.5670$$

Degree distribution: sport nodes logarithmic scale



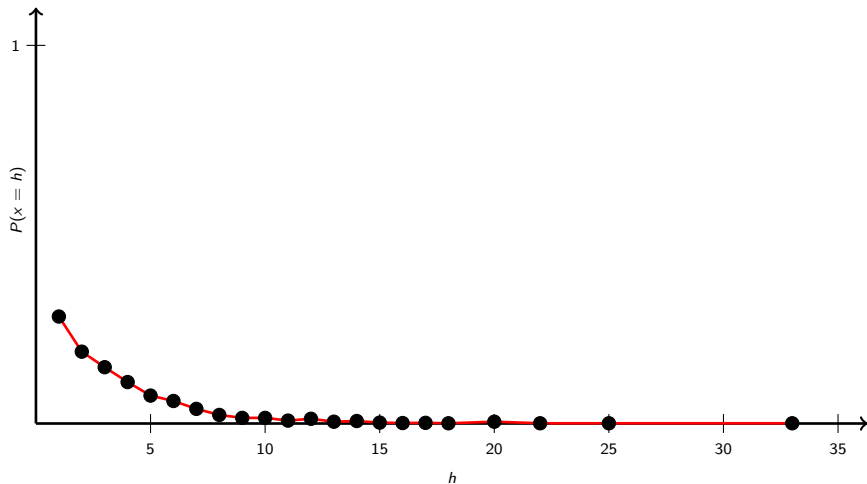
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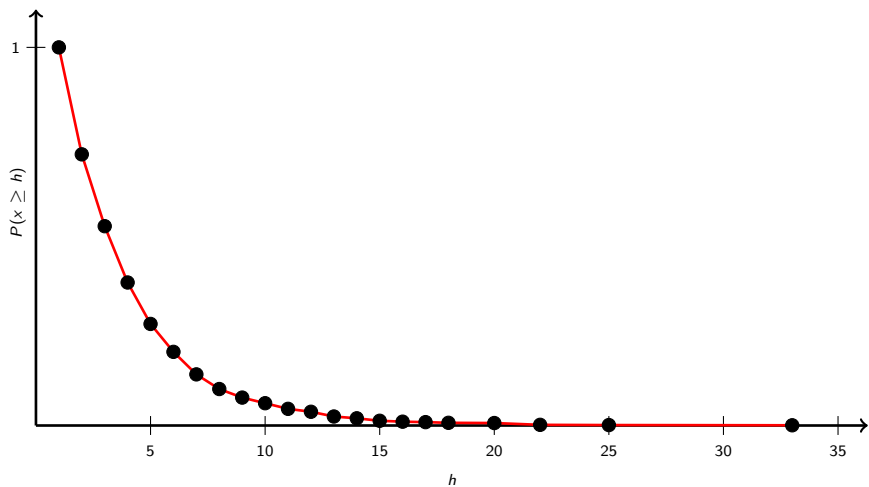
$$p\text{-value} = 0.5670$$

	bin.neg.		Poisson		exponential		Weibull		log-normal		Yule		power law + cutoff	
	LR	<i>p</i>	LR	<i>p</i>	LR	<i>p</i>	LR	<i>p</i>	LR	<i>p</i>	LR	<i>p</i>	LR	<i>p</i>
sport - nodes	4.14	0.00	4.09	0.00	4.31	0.00	0.13	0.89	-0.35	0.72	-0.004	0.94	-0.53	0.30

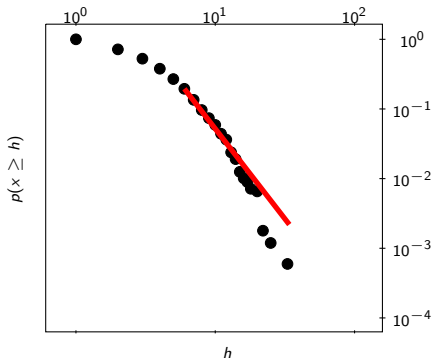
Degree distribution: athletes nodes



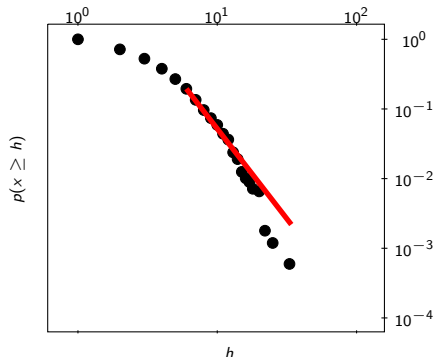
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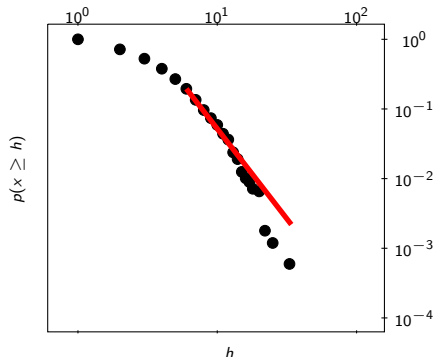


$$\alpha = 3.49$$

$$x_{\min} = 6$$

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Degree distribution: athletes nodes logarithmic scale



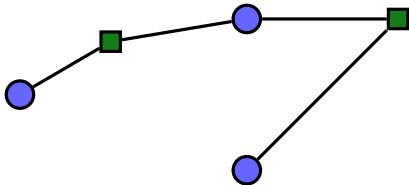
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	LR	p	LR	p	LR	p	LR	p	LR	p	LR	p	LR	p
athletes - nodes	3.73	0.00	3.09	0.00	-0.83	0.40	-2.16	0.03	-2.12	0.03	-3.94	0.00	-6.62	0.00

Nodes distance

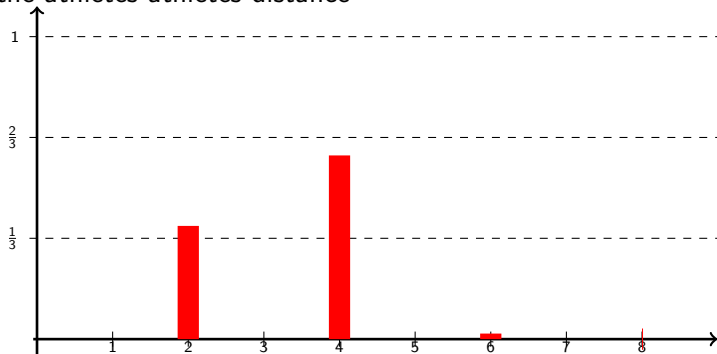


The maximum distance between every pairs of nodes in a graph is defined as the **diameter** of the graph. We observe a diameter of 8 but on average the shortest path between nodes is 3.33.

We are in presence of so called **small-world** phenomena.

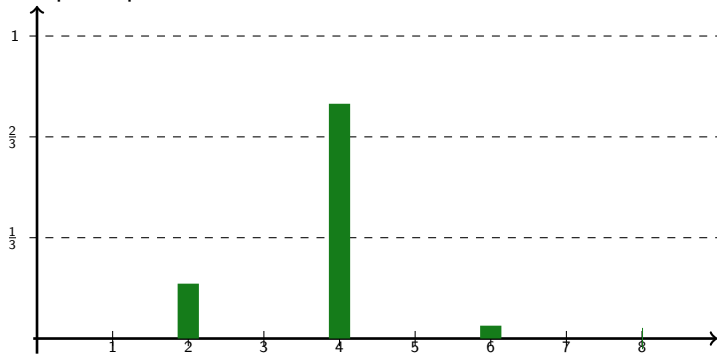
The distance distribution

the athletes-athletes distance



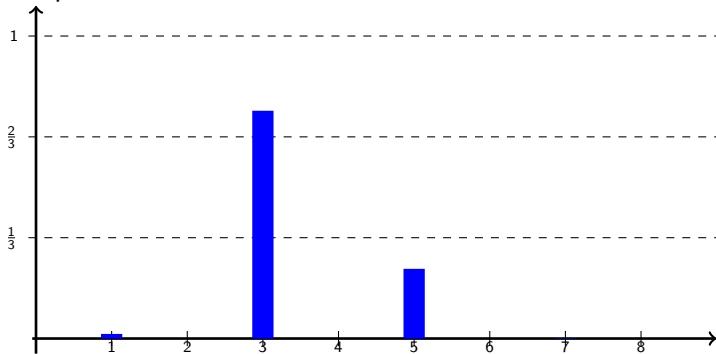
The distance distribution

the sport-sport distance



The distance distribution

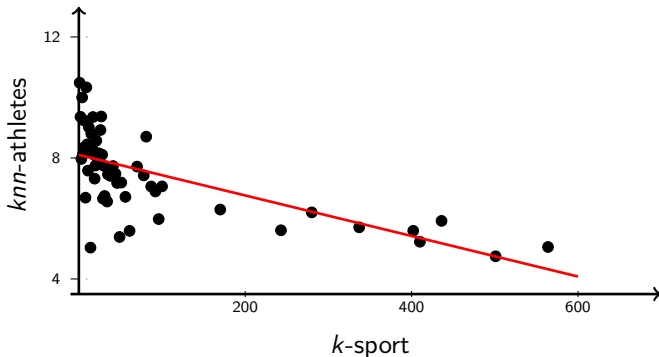
the sport-athletes distance



Assortativity in bipartite

We-sport network shows a **disassortative** behaviour: the Pearson coefficient is -0.2425 .

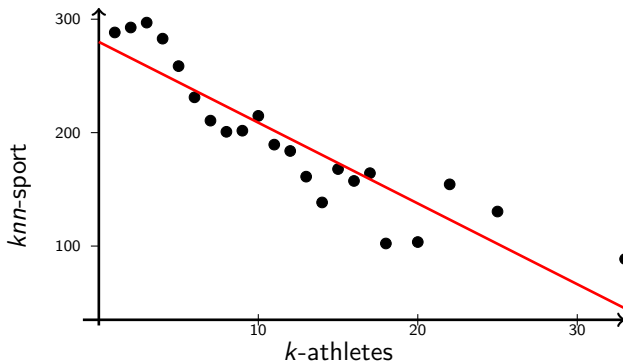
Moreover if we calculate the nearest neighbor degree:



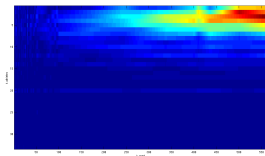
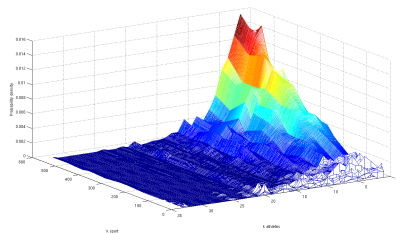
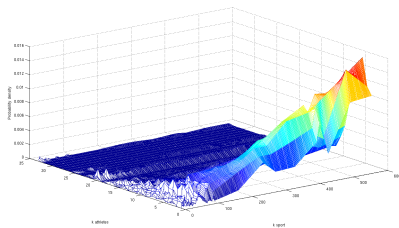
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The joint probability



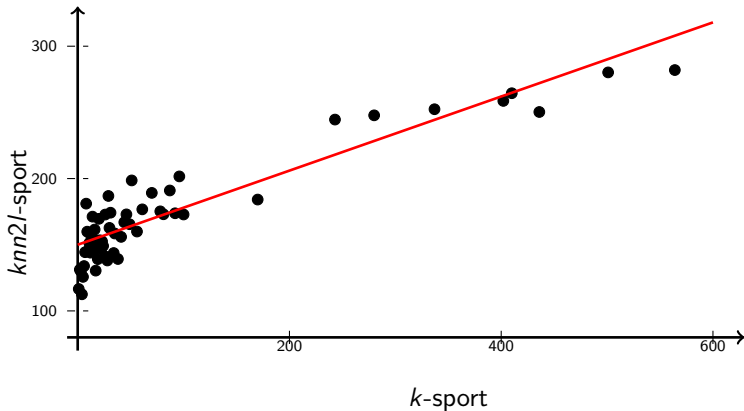
2-length assortativity in bipartite

We want to try to answer the question:

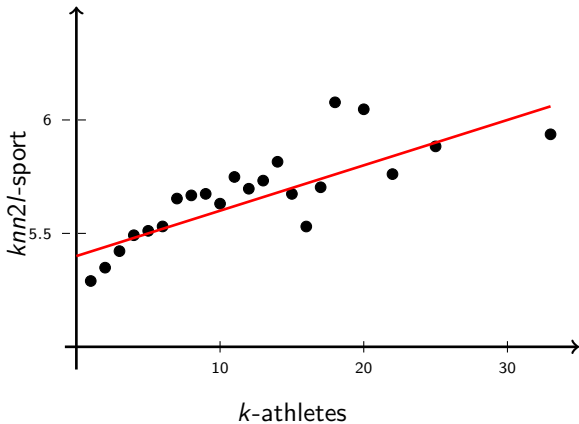
do people choose sports that connect them with similar people or not?

Therefore we analyze the 2-length assortativity: we observe a weak assortative behavior for athletes-nodes (0.0326) and stronger for sport-nodes (0.2620)

2-length assortativity in bipartite



2-length assortativity in bipartite



The Clustering Coefficient for Biparite Networks

Again in order to understand the aggregation behavior of athletes we try to understand if people prefer to connect with other sharing the same sport's preference. Hence we define a similarity matrix cc which counts for each couple of athletes the number of sports they share:

$$|N(v) \cap N(u)|$$

then we can normalize that matrix. Le Blond et al., Latapy et al., and Borgatti suggest the three following denominator:

- $\min(|N(v)|, |N(u)|)$ for $cc_{\bullet}(u, v)$

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The clustering coefficient II

From the similarity matrix we can calculate the clustering coefficient of each nodes.

$$cc(v) = \frac{\sum_{u \in N(N(v))} cc(v, u)}{|N(N(v))|}$$

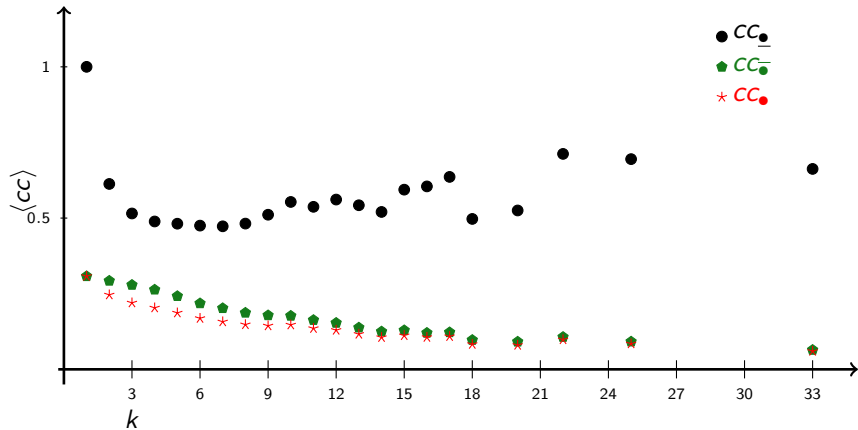
and from that the clustering coefficient of A -partition:

$$cc = \frac{1}{|A|} \sum_{v \in A} cc(v)$$

graph	cc_{\bullet}	cc_{\bullet}^{-}	cc_{\bullet}
athletes	0.6628	0.2672	0.2315
sport	0.4126	0.0615	0.0536

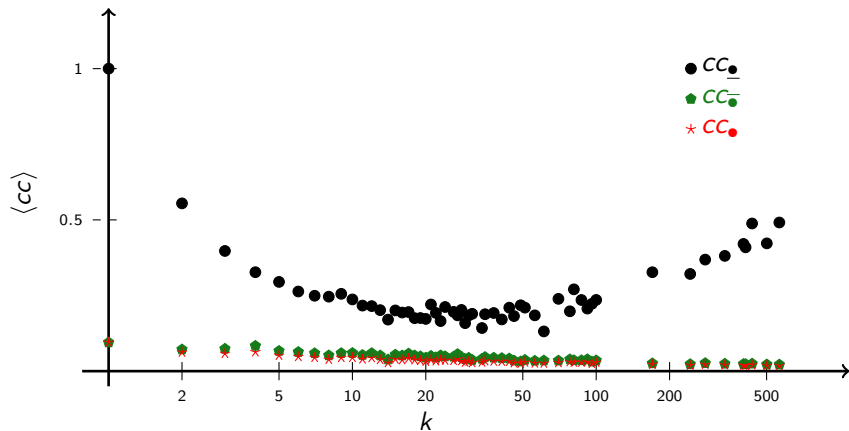
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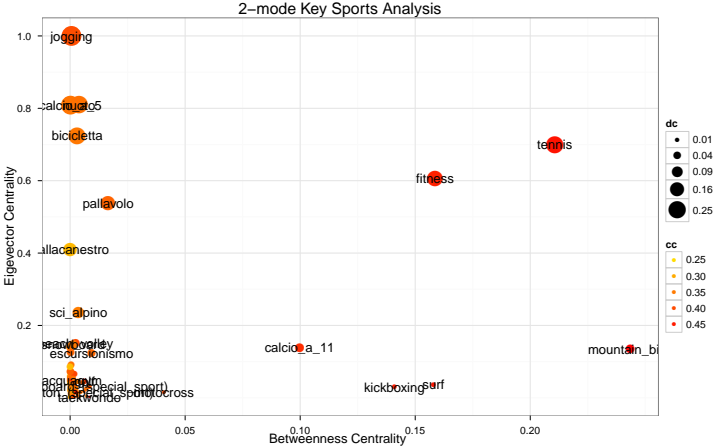
The athletes case



The clustering coefficient II

The sport case





An application: which is the best sport to meet girls?

Contacts

for further informations:

www.we-sport.com

or contact us:

luca.ferreri@unito.it

fabio.daolio@unil.ch